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Crop Competitiveness and Future Climate Change in the Northern Great Plains

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Abstract: We evaluate the regional-level agricultural impacts of climate change in the Northern Great Plains. We first estimate a non-linear yield-weather relationship for all major commodities in the area: corn, soybeans, spring wheat and alfalfa. We separately identify benevolent and harmful temperature thresholds for each commodity, and control for severe-to-extreme dry/wet conditions in our yield models. Analyzing all major commodities in a region extends the existing literature beyond just one crop, most typically corn yields. Alfalfa is particularly interesting since it is a legume-crop that is substitutable with grasses as animal feed and rotated with other row-crops for nitrogen-fixation of soils. Our model includes trend-weather and soil-weather interaction terms that extend the existing yield-weather models in the literature. Results suggest that temporal adaptations have not mitigated the negative impacts of weather stressors in the past, and that the spatial soil profile only weakly influences weather impacts on crop yields. We estimate yield-weather elasticities and find that historical weather patterns in the region have benefited corn and soybeans (spring wheat) the most (least). We expand our analysis to formally evaluate the role of short-run weather fluctuations in determining land-use decisions. We utilize decomposed crop yield estimates due to trend and weather in order to model crop acreage shares. Our preliminary results suggest that short-run weather fluctuations are an important factor for decisions on soybeans and spring wheat shares, however only yield trends drive corn shares.

Introduction and Motivation

A large body of literature in the areas of agronomy, economics and other social sciences has emphasized the agricultural impacts of climate change. Economists exploit exogenous changes in weather to identify its impacts on agricultural yields, profits and land-values. There is a growing research interest in national and regional agricultural impacts due to climate change because of uncertain and potentially large future productivity losses, and because of the availability of regional climate data. Corn has attracted most attention among economists who have studied the impacts of climate change on U.S. agriculture. Understanding the productivity dynamics of corn due to changed weather conditions is critical to U.S. agricultural exports, food and biofuel production. A few studies have also considered the weather-related dynamics of soybean and cotton yields (Schlenker and Roberts, 2009). Recently, Tack et al. (2015) estimated the effects of warming on 264 wheat varieties using field-trials data on yields.

Agricultural production in the eastern portion of the U.S. northern Great Plains, an expanse of about 100,000 square miles, has shifted towards corn and soybeans production in the past decade. We analyze county-level agricultural yields for the major commodities in two rain-fed states of the U.S. northern Great Plains: North and South Dakota. The agricultural economy of the Dakotas comprised of 51% cropland and 38% pasture/grassland in 2007 (United States Department of Agriculture (USDA) - Economic Research Service (ERS), 2011). Farm revenues from crop and livestock production in the Dakotas doubled between 2007 (\$750 mi.) and 2012 (\$1.5 bi.) (U.S. Census of Agriculture, 2007 & 2012). The doubling of farm revenue during this period can be attributed, at least in part, to increased corn/soy cultivation.¹ However, higher

¹ The average per bushel price increased by almost 50% for corn, from \$4.1 in 2007 to \$6.6 in 2012, as well as soybeans from \$9.6 in 2007 to \$14 in 2012.

corn/soy acreage came at the expense of almost 671,000 acres of grasslands replaced in the eastern Dakotas between 2006 and 2011 (Wright and Wimberley, 2013), along with wheat and small grains (Johnston, 2014). It is interesting that corn, which is a water-thirsty crop, has been significantly cultivated on these semi-arid lands where periodic droughts and intense flooding further degrade regional soils (National Climate Assessment, 2014)². The advent of new technology and improved land management practices might have offset the region's limited land quality by enhancing yields and sustaining farm revenues (Ojima *et al.* 2015; Parton *et al.* 2010).

Droughts and floods are already a significant phenomenon in the northern Great Plains and are likely to intensify in future (Kunkel *et al.* 2013; National Climate Assessment, 2014).³ Row cropping could benefit from increased winter precipitation leading to higher soil moisture reserves, but higher spring-time temperatures may offset such gains due to increased evapotranspiration. The National Climate Assessment has also reported longer average growing seasons (+24 days) by 2050 as compared to 1971-2000. Further, better technology may play a role in mitigating adverse climate change impacts. Historically, however, technological advancements have been asymmetric across Dakotas' commodities. For example, corn hybrids were developed as early as 1930s while only self-pollinated wheat varieties were used even until the 1970s. The corn R&D sector also experienced continued private sector investments while wheat's R&D sector was mostly public sector driven even until 1997 (Fernandez-Cornejo, 2004 p. 30-37). We investigate the different agricultural yield trends of the region's major crops with a

² Historically, wheat was a dominant crop in the Dakotas due to its tolerance to the region's semi-arid soils.

³ Ojima (2015) has reported that South Dakota has already experienced nine flood disasters during the 2000-'10 decade. Heavy rainfall events and droughts are expected to increase by 2071-2100 as a result of higher spring-time precipitation and drier summers.

view on the potential impact of asymmetric technological innovations in response to future climate change.

Since several crops are viable options for Dakotas' farmers we evaluate relative productivity of commodities in these states as weather patterns shift. To achieve this, we first model individual county-level annual yields as a function of beneficial and harmful weather outcomes during 1950-2013. We explicitly model extreme weather events like severe dryness and severe wetness. Flexible trends are incorporated as a proxy for technological innovations, and trend-weather interactions to better understand temporal adaptations to historical weather fluctuations. We also introduce soil-weather interactions to differentiate yield-weather outcomes by soil-quality. The spatial distribution of regional soils can be informative in predicting future land-use distributions.

Further, we differentiate the impacts of an isolated, single-day heat event from consecutive two-to-three-day, and four-or-more-day events. This is important since average temperatures are expected to rise by 2.5-13°F in 2100, when compared to 1960-'70 levels, potentially leading to more frequent and intense consecutive heat events that adversely affect crop yields (Karl *et al.* 2009, Ojima *et al.* 2015). We also assess the impact of humid conditions on crop yields as they precede extreme events like tornadoes (Ojima, 2015), usually causing destruction to life and capital.

We estimate yield-weather elasticities from our yield-weather models to evaluate relative competitiveness among commodities due to past weather outcomes. This is relevant because the weather conditions in a particular year may have asymmetric productivity implications across commodities. We extend this idea to a formal model of within-cropland shares as a function of

relative profitability of crops that is attributed to the short-term weather realizations. To the best of our knowledge, this is the first study to analyze all of a region's major crops that includes alfalfa, which is a proxy for the grasses. The trend-weather and soil-weather interactions, and differentiating isolated and consecutive heat events is also new to the existing yield-weather models. Our modelling framework of regional land-use transitions based on crop competitiveness due to short-run weather impacts is also novel to this literature.

This paper is subdivided into several sections. A literature review section provides a brief summary of the literature on climate change impacts on agricultural yields. This is followed by a data section where we discuss data sources and processing. The methodology section presents our yields model with various considerations. We then describe crop competitiveness due to yield-weather interaction and present a framework that models land-use switching by using the yield estimates. We then briefly discuss our results and outline future work for this study.

Literature Review

Agricultural Yields and Historical Weather Outcomes

Schlenker and Roberts (2009) estimated step-functions, piecewise-linear functions, and eighth-order polynomials to characterize a non-linear relationship between crop yields and temperature during 1950-2005. Yields were found to increase modestly within the benevolent temperature thresholds and sharply fall beyond a higher temperature threshold. Their functional specification matched the agronomic concept of yield dependence on yields and thus provided better forecast accuracy than earlier model specifications. Other control variables that the authors included were precipitation, precipitation-squared, county-fixed effects and quadratic trends.

Butler and Huybers (2012) investigated the effect of spatial adaptation on yield losses due to warming. They modelled corn yields against accumulated benevolent (hereafter growing-degree-days or *GD*), and harmful (hereafter stress-degree-days or *SD*) temperature levels, that is a concave functional form of yield dependence on heat.⁴ By controlling for spatial variation in *SDs*' impact on corn yields, they found that predicted yield loss due to 2°C warming could reduce from 14% to 6%. The authors included a linear trend variable in their models, but did not control for moisture availability.

Xu *et al.* (2013) also utilized degree-days to characterize yield response to temperature to establish the benefits of adopting genetically-engineered corn and soybean varieties. However, they used the quadratic form of a Palmer's Z index, instead of precipitation, to control for moisture availability for crop growth. Palmer's Z better reflects the supply and demand imbalances in moisture availability because it controls for evapotranspiration along with precipitation (Karl, 1985).

Recently, Massetti and Mandelson (2016) have focused on the impact of extreme weather events like heat waves, cold waves, hail and tornados on corn and soybean yields. They estimate step function to estimate yield response to each 3°C temperature bin and find that including weather extremes reduced the harmful impacts of higher temperatures. From here, they argue that the effect of various temperature levels is not time-separable and that high temperatures occurring for several days in continuum are more harmful than that for several hours. We capture such impacts in our paper through the aforementioned disaggregation of stress degree-days.

⁴ We provide a detailed discussion on this concave yield-temperature relationship capture by *GDs*, *SDs*, and on the step-functions in the 'Methodology' section.

Tack *et al.* (2015) studied the impacts of warming on wheat yields in the U.S. The study utilized a unique trial-based dataset of the 264 seed varieties to understand the weather dynamics of wheat yields. Extreme spring-time heat is found to reduce yields. Newer seed varieties give better yields but are less heat resistant than the older ones. Alongside, increased rainfall was reported to have offset the impacts of warming on wheat yields.

Auffhammer *et al.* (2013) pointed towards various pitfalls of using climate data. The one relevant to our study is the importance of spatial correlation in the data. The authors suggested utilizing a procedure developed by Conley (1999) to control for cross-sectional or spatial dependence of standard errors. Ortiz-Bobea (2013) stressed on the importance of within-season input-use adjustments by farmers due to weather variations and suggested including seasonal disaggregation of the weather variables when modelling yields.

So as to capture uncertainty in future climate forecasts Burke *et al.* (2015) emphasized the variations in climate projections from over 20 climate models. This study's extensive literature review revealed that the econometrics of historical weather impacts have advanced, while the forecasts based on them still entail only two climate model-outputs (median). The authors found that the variance of predicted climate impacts was sufficient that just relying on one or two of these would mislead policy. In particular, they found that climate uncertainty changed the extremes of the projected outcomes dramatically, with overoptimistic outcomes (extreme-left of the distribution).

Methodology

→Crop Yields and Historical Weather Outcomes

Data

We construct a dataset that combines historical county-level agricultural yields, daily minimum and maximum temperature and precipitation. To these county-level data, we join monthly Palmer's Z indices that are available for Dakotas' climate divisions, and the survey-based time-invariant county-specific soil quality. The time-span of our analysis is 1950-2013. We now provide a detailed description each of dataset used for this study along with relevant variable summaries.

We use annual county-level crop yields data from 1950 to 2013 for 119 counties in the Dakotas, downloaded from National Agricultural Statistical Service's (NASS) QuickStats 2.0 portal. These are survey based estimates of expected yields, calculated as weighted ratio of total production divided by total planted acreage of a crop. The weights are assigned according to respondent density in an agricultural statistical district (S.M.B., USDA-NASS, 2012). Figure 1 presents standardized historical yields for all major crops in the Dakotas. Notably, among the four crops alfalfa had the highest yields in 1950 and lowest in 2013. Corn seems to have sustained strongest trends amongst all four commodities, which could be due to the aforementioned emphasis on the R&D of this crop. Further, the four most prominent dips for all crops in 1977, '88, 2002 and '12 are driven by droughts, in line with Massetti and Mandelson (2016) who found droughts to be the most harmful to corn and soybean yields in the eastern U.S.

We now turn to describing our weather variables that can be characterized in two categories: heat and moisture.

1) *Heat*: We use county-level daily temperature fluctuations to evaluate the causal impact of weather on yields. The daily minimum and maximum temperatures for each county are obtained as weighted averages of near-by weather station values, where weights are the inverse-distances between counties and stations-squared. We aggregate the daily temperature levels into threshold-

based seasonal heat exposure variables called degree-days. The beneficial temperature levels are aggregated into growing degree days or the *GDDs*, and harmful temperature levels into stress degree-days or the *SDDs*. We borrow the mathematical representation for *GDDs* and *SDDs* from Xu *et al.* (2013). That is, *GD* for month m in year t can be written as $GD_{m,t} = \sum_{d \in m} 0.5 \left(\min \left(\max \left(T_d^{\max}, T(l) \right), T(h) \right) + \min \left(\max \left(T_d^{\min}, T(l) \right), T(h) \right) \right) - T(l)$, where $T(l)$ and $T(h)$ are lower and upper thresholds of the beneficial temperature range; T_d^{\max} and T_d^{\min} are maximum and minimum temperatures on days d in month m . Similarly, *SD* for month m in year t can be written as $SD_{m,t} = \sum_{d \in m} 0.5 \left(\max \left(T_d^{\max}, T(k) \right) + \max \left(T_d^{\min}, T(k) \right) \right) - T(k)$, where $T(k)$ is the temperature threshold at which higher temperatures are modelled to decrease crop yields. We describe the identification of these three temperature thresholds in is discussed later.

2) Moisture: To incorporate moisture into our yield models, we use monthly variations in Palmer's Z index (denoted *Z hereafter*). Monthly Z values vary across climate divisions (cross-sections) and each climate division may consist of multiple counties. The data are available from National Oceanic and Atmospheric Administration between 1895 and 2013. Counties that are fully contained into a climatic division, are assigned its Z values each period. Whereas the counties that are shared among more than one climate divisions, are assigned area-weighted Z values each period. By definition, Z is a categorical variable that measures short-term moisture availability with monthly observations. We prefer Palmer's Z to precipitation because it better captures actual available moisture towards plant growth. It measures soil moisture deficiency accounting for precipitation as well as evapotranspiration and soil water storage. Note that, Z accounts for evapotranspiration by using monthly and annual temperature means and may be

correlated with our heat measures. Table 1 summarizes various categories of moisture availability characterized by Z .

To capture a non-linear yield response to moisture (in line with heat measures above), we define $DRYZ_{i,m,t} = -\min(Z_{i,m,t} + 1.99, 0)$ and $WETZ_{i,m,t} = \max(Z_{i,m,t} - 2.49, 0)$ for each county i in month m of year t , where $Z_{i,m,t}$ is the observed value of the index. $DRYZ$ and $WETZ$ will be used in our yield models to capture the impact of moisture availability towards crop productivity. The response estimates of these variables will be interpreted as impact of a severe-to-extreme drought (or wetness) on yields relative to a moderate moisture deficiency scenario. We discussed the impact of droughts on yield trends earlier. Wetness is further interacted with the SDs to evaluate the impact of humidity on agricultural yields.

An alternative moisture index to Z is the Palmer Drought Severity Index ($PDSI$) that is often used to capture moisture deficiency (e.g. Massetti and Mandelson, 2016). However, we rely on Karl (1986)'s recommendation to use Z over $PDSI$ to capture short-term moisture deficiencies because of its stability across calibration periods.

We utilize the National Resource Inventory (NRI)'s land capability subclasses to evaluate how soils interact with weather conditions to impact crop yields. The land capability classification assigns progressively unsuitable soils into higher classes.⁵ Typically, class I soils can be readily subject to cropping; class II, III & IV lands require some additional remedies before they can be cropped; and categories (V-VIII) are usually inappropriate for cropping. The extent and type of remedies required for class II, III & IV lands depends on the type of impediment(s). Land

⁵ Soils under higher land capability categories require more intense management practices to mitigate intrinsic limitations towards agricultural production.

capability classes II-VIII are further sub-categorized by the soil's dominant impediments. These sub-categories are vulnerability to erosion, excess wetness (or poor drainage), root-zoning limitations (dry, shallow soils) and climatic limitations. The NRI follows a hierarchical nomenclature in assigning these sub-categories if multiple impediments are present. Erosion $[E]$ takes precedence over every other kind. Next, in this ordering are excess wetness $[W]$ and dry/shallow soils $[S]$. Soils are assigned a climatic limitations category $[C]$ only if temperature and/or moisture-deficiencies are the only impediments to cropping. This means that $[W]$ might imply shallowness as well as poor drainage limitations but poor drainage is the dominant limitation. Similarly, $[E]$ could imply shallowness and/or poor drainage along with erosion as impediments, where erosion is the dominant limitation towards cropping. The data does not differentiate between soils with single and multiple impediments.

We utilize the $[S]$ and $[W]$ sub-categories in our yield models, where $[S]$ is not confused with any other category. We constrain our analysis to land capability classes II-IV as they support about 85-90% of crop acreage in the Dakotas. In our yield models, we include soil-weather interactions. That is, we use percent land in a county under $[S]$, denoted $\%LCC234[S]$, and interact it with SD , GD , $DRYZ$ and $WETZ$. These interactions are expected to reveal whether specific soil limitations could mitigate or aggravate heat/moisture impact on yields. We hypothesize that the yield impacts of SD will be aggravated due to shallow soils, while that of $WETZ$ might be mitigated (*relative* to $[W]$). Further, the impacts of extreme wetness could be worsened on soils under $[W]$ sub-category.

Identifying crop-specific GD and SD thresholds

Roberts and Schlenker (2009) characterized the crop yields dependence on temperature using a non-linear, concave relationship. Such a temperature-dependence relationship has been adopted

by the studies that followed, for example Butler and Huybers (2012), Xu et al. (2013), and Massetti and Mandelson (2016). In particular, the non-linearity implies an intermediate range where higher temperatures are benevolent to crop yields. Beyond that the impact of higher temperatures plateaus out, before eventually becoming negative above a high threshold. This functional form is based on the agronomic concept of *GDs* and *SDs* (described in the data section earlier). We too characterize yield-temperature relationship using *GDs* and *SDs*. Note that the underlying temperature thresholds for spring wheat and alfalfa remain unidentified in the literature. Although studies have previously identified such thresholds for corn and soybeans, there is no reason to believe that they are transferable across crop-types. This is because crop phenology varies greatly across crop varieties, and so do their respective growing seasons. This is also reflected in Roberts and Schlenker (2009) where beneficial and harmful temperature thresholds vary across various crops. The growing conditions are also region-specific. Therefore, we identify these thresholds for all of Dakotas' major crops.

We implement a two-step strategy to identify *GD* and *SD* thresholds that are crop-specific. In the first step, we utilize variations in daily average temperatures to estimate a step-function of marginal yield response to each crop's seasonal exposure to 3-degree Celsius bins, controlling for quadratic trends and quadratic precipitation. For all crops, we find a positive marginal yield response within the 12-15°C range and a negative response for temperatures above 32°C. We then introduce 1-degree Celsius bins, except for 12-15°C and above 32°C, to achieve refined cut-offs for *GDs* and *SDs*. The step-functions are presented in figures 2-5. The cut-offs derived here are considered to be preliminary as they may be biased due to excluded explanatory variables and only a guide to the second step in their identification. In the second step, we refine the preliminary cut-offs using regressions loops to maximize the fit of a 'full' model. The full model

for this purpose is described below in equation 1, and the finalized *GD* & *SD* thresholds along with crop-specific growing seasons are listed in table 2. Further, variable summaries are provided in table 3. We next discuss the yields model upon which these looped regressions are performed.

The yield-weather model is given as

$$Yields_{i,t} = \beta_0 + f(t) + \beta_W W_{i,t} + \beta_{tW} t W_{i,t} + \beta_{SW} Q_i W_{i,t} + \varepsilon_{i,t} \quad (1)$$

Equation (1) represents a linear regression-model that establishes a relationship between crop yields $Y_{i,t}$ and a vector of historical weather outcomes $W_{i,t}$. $f(t) = \sum_{k=1}^3 D_k \{ \beta_1^k (t - t_k) \}$, with $t = 1$ for year 1950 and $= 64$ for 2013, specifies trend impacts on yields as continuous, linear splines to allow different slopes at pre-assigned spline-knots or break-points. Here, the regression splines are characterized by an indicator variable $D_k = 1$ if $t \geq t_k$ or 0 otherwise; and a set of spline-knots $t_k \in \{1965, 1980, 1995\}$. Trend is intended to control for the impact of evolving land management practices and technological innovations on crop yields. The knots are chosen to capture a shift in trend-impacts due to exogenous policy, e.g., 1996 Freedom-to-Farm Act, or changes in federal subsidy and a decline of commodity prices in mid-80s (Schlenker et al. 2006, p. 119).⁶ The weather outcomes' vector $W'_{i,t} = [GD_{i,t}, SD_{i,t}, DRYZ_{i,t}, WETZ_{i,t}]$ captures the concave yield response to heat and moisture deficiency. The variables $WETZ_{i,t}$ and $SD_{i,t}$ are interacted to estimate the impact of humidity on agricultural yields.

⁶ We ruled out decadal knots because an F-test found the goodness-of-fit normalized by the loss of degrees of freedom due to decadal knots over 15-year knots did not improve significantly.

We include trend-weather interactions to control for the impact of temporal adaptations to historical weather fluctuations. For example the coefficients for $t \times SD_{i,t}$ measure how temporal adaptations mitigate or aggravate the harmful impacts of $SD_{i,t}$. Since trends potentially capture the impact of new technologies on yields, we hope that trend-weather interactions will give useful insights on how technological innovations modify weather impacts. The vector of weather variables is also interacted with soil quality, $Q_i = [\%LCC234[S]_i, \%LCC234[W]_i]$. These interactions are intended to capture the role of soil limitations on the yield-weather relationships. We conjecture that the droughty (wet) soils would potentially aggravate the harmful impacts of SD ($WETZ$). However, it is important to note that $\%LCC234[S]_i$ represents percentage of drought soils in county i , not distinguishing what is grown on this soil-type. The consequence of this data-driven limitation is that we cannot attribute the coefficient estimate to crop-specific yield impacts. Rather we can only provide a generalized view on the role of soil quality when the sign of corresponding coefficient estimates is same for all *major* crops. Also, we will be limited to only qualitative inference (positive or negative).

SD categorization

To differentiate yield impacts by the intensity of heat stress, we disaggregate the stress degree-days into isolated or single-day events (SD^I), and continuous events of two-three-consecutive-days (SD^{23}) and four-or-more-consecutive days (SD^{4+}). Our motivation here is two-stranded: 1) understand whether an isolated SD s have different effects if they occur early in the growing season; 2) understand the impact of more frequent heat events as per future climate projections.

We disaggregate total seasonal SD into SD^I , SD^{23} and SD^{4+} categories, such that $SD = SD^I + SD^{23} + SD^{4+}$. The $SDDI$ variable is constructed by multiplying the column of SD s with an

indicator variable that equals 1 on an isolated hot day or 0 otherwise. SD^{23} and SD^{4+} are constructed in similar fashion. Now, heat may not accumulate proportionately within each SD category. In addition, SD^I may be a more/less frequent event than SD^{23} , which it turn may be more/less frequent as compared to SD^{4+} . To compare coefficients across SD categories, we normalize them such that SD^{23} (or SD^{4+}) represents a bundle of 2-or-3 (or 4-or-more) SD^I s, in a consecutive sequence rather than in isolation. See the appendix for a formal description of normalization.

Seasonal Disaggregation

The purpose of seasonal disaggregation is to allow for input-adjustments by farmers due to unexpected within-season weather fluctuations. The basic yields' model assumes perfect foresight for seasonal weather outcomes as far as input-decisions are concerned. It fails to control for a scenario where a farmer may decide to use extra fertilizer half-way through the season to make up for the losses due to unanticipated extraordinary wetness. The impact of early season heat may correspond to isolated heat events from above specification, since most SD^I s occur during the early growing season.

→Annual Weather Realizations, Crop Competitiveness and Land-Use Change

For a profit-maximizing representative landowner who may allocate his/her land towards more than one viable land-use, the optimal allocation is when marginal return of an extra acreage is equal across land-use types. Marginal return to a crop's land allocation would depend on exogenous factors like weather, soils, etc., endogenous inputs like fertilizers, pesticides, etc., and the input & output prices. If the market prices are assumed to be constant and the endogenous inputs independent of the crop's acreage allocation, then good (bad) weather will increase

(decrease) its yield, thereby making the crop more (less) profitable. If such weather impacts are asymmetric across Dakotas' major commodities, they can potentially trigger landowner adaptations by increasing the acreage allocation of the most profitable crop(s). We draw from this argument to evaluate crop competitiveness that relates regional land-use changes to historical weather. Growing season and temperature thresholds differ across crops in our study. In order to make inference about crop competitiveness we calculate yield elasticities to weather as they are a unit-less measure, and thus comparable across crops.

A conceptual framework that extends relative crop competitiveness, as measured by yield-weather elasticities, to formally model annual land-use decisions is visualized in figure 7. Specifically, we model land-use share, $s_{i,t}^l$, for crop l in county i in year t such that $l \in A$ where $A \in \{\text{corn, soy, spring wheat}\}$ is the set of commodities analyzed. The modelling strategy that restricts shares between 0 and 1 is to assume a random regression error term that is extreme-value distributed. Therefore, we have

$$s_{i,t}^l = \frac{\exp(\pi_{i,t}^l)}{\sum_{k \in A} \exp(\pi_{i,t}^k)}, A \in \{\text{corn, soy, spring wheat}\} \quad (2)$$

Equation (2) specifies the estimation framework of county-level land-use shares for the Dakotas' major row crops, i.e. corn, soybean and spring wheat. The explanatory variables are the per-acre returns for each crop-type that also include government payments in the form of crop-specific insurance subsidies, disaster payments, and other farming subsidies. We will also include county fixed-effects to control for county-specific factors like soil quality, demographic characteristics, etc.

We specify per-acre returns as $\pi_{i,t}^l = \pi_{i,t|f(t)}^l + \pi_{i,t|\widehat{W},S}^l$, where $\pi_{i,t|f(t)}^l = P_t^l \widehat{Y}_{i,t|f(t)}^l - C_t^l$ and $\pi_{i,t|\widehat{W},S}^l = P_t^l \widehat{Y}_{i,t|\widehat{W},S}^l - C_t^l$. To evaluate these decomposed returns, we utilize *predicted* yields $\widehat{Y}_{i,t}^l$, region-level market price P_t^l , and the region-level production cost C_t^l . In order to identify short-term weather impacts on land-use, decompose the predicted yields $\widehat{Y}_{i,t}^l$ into

$$(a) \widehat{Y}_{i,t|f(t)}^l = \widehat{f}(t), \text{ and} \quad (3)$$

$$(b) \widehat{Y}_{i,t|\widehat{W},S}^l = \widehat{\beta}_W \widehat{W}_{i,t} + \widehat{\beta}_{SW} Q_i \widehat{W}_{i,t}.^7 \quad (4)$$

Note that utilizing *predicted* weather to predict yields towards land-use decisions emphasizes the random weather events that are likely to be unobserved to the decision-maker as well. To obtain

$\widehat{W}_{i,t}^l$, we assume an AR(4) process for period t weather outcome and estimate

$$\widehat{W}_{i,t}^l = \widehat{\gamma}_o^l \mathbf{1} + \widehat{\gamma}_t^l t \mathbf{1} + \left[\sum_{k=1}^4 \widehat{\gamma}_{W,k}^l W_{i,t-k}^l \right] \mathbf{1}, \quad (5)$$

where $\widehat{\gamma}_{W,k}^l = [\widehat{\gamma}_{GDD,k}^l, \widehat{\gamma}_{SDD,k}^l, \widehat{\gamma}_{DRYPZ,k}^l, \widehat{\gamma}_{WETPZ,k}^l]$, $W_{i,t}' = [GDD_{i,t}, SDD_{i,t}, DRYPZ_{i,t}, WETPZ_{i,t}]$ and $\mathbf{1}'$

$= [1, 1, 1, 1]$.⁸ Further, P_t^l and C_t^l , from USDA-ERS's 'Commodity Costs and Returns' data

products, are available annually for the Great Plains region, so are invariant across counties.

Period t prices and costs are assumed to represent landowner expectations of county-specific

⁷ Coefficients of trend-weather interaction variables are assumed to be zero in order to achieve the proposed decomposition of predicted yields.

⁸ The estimation results along with the econometric considerations like non-stationarity are presented in an appendix.

market valuations of production inputs and output. Hence, the reduced form land-use shares regression is written as

$$\ln\left(\frac{s_{i,t}^l}{1-s_{i,t}^l}\right) = \sum_l \beta_\pi^l \left\{ \alpha \cdot \hat{\pi}_{i,t|f(t)}^l + (1-\alpha) \cdot \hat{\pi}_{i,t|\widehat{W},s}^l \right\} + \sum_l \beta_{GP}^l \widehat{GP}_{i,t}^l + \varepsilon_{i,t}^l, l \in A \quad (6)$$

Parameters α and $(1-\alpha)$ in equation (6) designate the relative weightage attributable to impact of yield trends *versus* random weather fluctuations on land-use shares among the three major crops of this region. It is important to understand the weight landowners have placed on short-term weather outcomes in past and whether they are as important as higher returns due to trends that capture the advent of better technology and land-use management practices. In addition, the substitutability among corn, soybeans and spring wheat is captured by own- and cross-profit elasticities of each crop's land-use share. Government payments are found to be critical to land-use decisions. Crop insurance subsidies are found to reduce risks of crop failure (Claassen *et al.* 2011, Miao *et al.* 2014) that are very much relevant for the Dakotas' marginal soils and climate. The land allocations are likely endogenous to insurance subsidies and other form of government payments. To control for this, we implement a two-step IV modelling strategy. We first model each form of government payment as a function of the expectation of market prices, weather, i.e.

$$\widehat{GP}_{i,t}^l = \hat{\lambda}_0^l + \hat{\lambda}_P^l P_t^l + \hat{\lambda}_{\widehat{W}}^l \widehat{W}_{i,t}, \quad (7)$$

where $\hat{\gamma}_{\widehat{W}}^l = [\hat{\gamma}_{GDD}^l, \hat{\gamma}_{SDD}^l, \hat{\gamma}_{DRYPZ}^l, \hat{\gamma}_{WETPZ}^l]$, $W_{i,t}' = [GD_{i,t}, SD_{i,t}, DRYZ_{i,t}, WETZ_{i,t}]$. Note that we

require our proposed instruments to be uncorrelated to $\varepsilon_{i,t}^l$, which will likely hold since they are controlled for through the period t predicted per-acre crop-specific returns. Finally, we utilize the

seemingly-unrelated regressions framework to estimate (6) as common regressors may lead to correlated system errors. The set of regressions in equation (6) are the second-step where the instrumented government payments in (7) are utilized.

Estimation Results

We present the regression estimates from fixed-effects panel regression, where the fixed-effects are due to varied soil quality across counties. We first discuss the estimation results from a basic (parsimonious) model in equation 1 each individual commodity and then, relative competitiveness. This is followed by differentiated *SD* impacts and seasonally disaggregated weather impacts on yields. We also present a robustness analysis.⁹

We find positive marginal yield trends for all commodities, except for alfalfa yields that are found to have stagnated during 1950-2013 (see figure 6). Further, the marginal impacts of trends are positive for all four commodities post-1995, and negative during 1980-'95. The post-1995 positive trends can be attributed to the Freedom-to-Farm Act of 1996 that gave farmers the flexibility of cropping choices according to market valuations rather than their farming history. Higher returns, as a result, would potentially encourage adopting newer and better technologies/management-practices eventually resulting in higher productivity across commodities. A similar, but reverse, trend during 1980-'95 could be a result of decrease in commodity prices in the mid-80s. For a comparison of trend-effects across commodities we plot normalized marginal effects in figure 5. We find the strongest trend-effects for corn during 1950-2013, followed by spring wheat, soybeans and alfalfa. In fact, yields increased more rapidly for spring wheat than corn

⁹ Note that spatial correlation among regression residuals is yet to be controlled for, but most estimated coefficients are highly significant anyway.

during 1950-'64, before being eventually overtaken in 1972. This fact correlates with higher R&D focus and adoption rates of hybrid and genetically engineered varieties for corn than wheat (discussed earlier, Fernandez-Cornejo, 2004 p. 30-37; Xu *et al.*, 2012).

The coefficient estimates for weather outcomes – *GD*, *SD*, *DRYZ* and *WETZ* – confirm a non-linear, concave relationship between yields and weather (see Table 4). In addition, we find that the rate of decline in yields due to temperature levels above the *SD* threshold is higher than the rate of increase due to higher temperatures in the *GD* range. This finding is consistent with Roberts and Schlenker (2009)'s, but we extend it to two more commodities – spring wheat and alfalfa. The case of alfalfa is particularly interesting because it is a legume crop, often grown for animal feed, for soil's nitrogen-fixation and is usually rotated with row crops like corn. Further, we find severe-to-extreme droughts to be the most harmful weather phenomenon in each case. This finding is consistent with Massetti and Mandelson (2016), but again extended to spring wheat and alfalfa as well. However, severe-to-extreme wetness caused only wheat yields to decline (less harmful than drought but more harmful than the *SDDs*). Whereas soybean and alfalfa yields benefitted from marginal increase in *WETZ*, with an insignificant, positive impact on corn. The non-decreasing impact of *WETZ* on corn and soybeans can be attribute to these crops' high water demand for growth. Alfalfa also potentially uses soil moisture as Helm (1993) suggest that it can lead to reduced moisture in the soils if grown in multiple rotations. We also find that humidity ($WETZ \times SD$) is beneficial to all crops' yields. Surprisingly, the coefficient to $DRYZ \times SD$ is also positive, significant which we cannot reconcile.

The trend-weather interactions reveal a positive, significant coefficients on trend-*GD*, and negative, significant coefficients on trend-*SD*, trend-*DRYZ* and trend-*WETZ*. This result holds true for all crop-types, except for soybeans where the trend-*DRYZ* coefficient is positive and

significant. The above discussion points out to potential correlations between higher yields and technological advancements through the trends variable. In that sense, we find that climate stressors reduced yields even in light of advances in technology, where one would expect the opposite. However, this interpretation is susceptible to correlations between trends and weather variables.¹⁰

Lastly, the soil-weather interactions reveal a weak relationship between soil limitations and weather outcomes. Recall that soil variables represent the percentage of a particular soil cover in a county, and not which crop was grown on that soil-type. Therefore, we can only provide a qualitative inference and we consider the impacts of all four major crop-types at once. We find that coefficient on $\%LCC234[S] \times SD$ is negative across all commodities (Table 4). This means that shallow soils aggravate the negative impact of SD s. However, these coefficients are not always significant, and hence only a weak impact. We also find that wet soils, with poor drainage, cause weak reduction (aggravate) in the positive (negative) impacts of $WETZ$.

SD categorization and Seasonal disaggregation

Table 5 presents the yield impacts of isolated vs. continuous heat events. The idea is to differentiate the impact of harmful heat (SD) by its intensity. We disaggregate the quantum of SD s into isolated or single-stress-degree-day (SD^I); two-to-three consecutive SD s (SD^{23}) and four-or-more SD s (SD^{4+}). We find that higher heat intensity causes more harm to crop yields. That is, the marginal impact of SD^{4+} is greater than that of SD^{23} and SD^I . Further, not only are

¹⁰ We find the correlation between GD and trends to be statistically insignificant, in the case of corn. This can be due to the fact that growing seasons are fixed in this study, while the distribution of temperatures might have become more disperse rather than scaling up. SD and trend are found to be negatively correlated, however the correlation coefficient was smaller than the regression coefficient.

isolated heat events least harmful to crop yields, they are, in fact, beneficial to spring wheat and soybean yields. The fact that low-intensity *SDs* enhance soybean and spring wheat yields while high-intensity *SDs* reduce them is akin to '*hormesis*', a toxicological phenomenon. Hormesis occurs when low-doses of an agent are beneficial while higher-doses may be toxic or lethal.

The seasonality of yield-weather responses provide some useful insights (Tables 6, 7). The positive yields response to early-season *SDs*, in case of spring wheat and soybeans, mirrors that of isolated *SDs*. This is because isolated *SDs* mostly occur in the early growing season (mid-April to Mid-June). In case of spring wheat, late-season *GDs* are found to be detrimental to yields, even when early-season *SDs* are beneficial. In addition, *GD* and *SD* thresholds are the lowest for spring wheat. This suggests that to model non-linear temperature effects, seasonal differentiation of heat would be more relevant than the usual thresholds-based characterization in case of county-level spring wheat yields. Further, we find higher spring-time wetness to aggravate the harmful effects of warming on spring wheat yields, which is in dis-agreement with the field-trials by Tack *et al.*, 2015. This could be a result of different yield-weather responses from the controlled-environment of field-trial yields and the real-world county-level yields, especially when the Dakotas experience extreme (dry/wet) growing conditions rather frequently along with limited soil quality. Also, interestingly, droughts are found to be more detrimental to yields when they occur late in the growing season for all commodities, except spring wheat. Further, high late-season *WETZ* in conjunction with high *SD* ($WETZ \times SD$) are beneficial to corn and soybean yields while being harmful early in the growing season. This could be because severe wetness can delay planting of the crop, thereby effectively reducing the length of growing period. Further, severe wetness and high humidity are beneficial (harmful) to alfalfa (spring wheat) through their May-April growing season.

The yield-weather elasticity estimates are presented in table 8. Soybean yields are found to be most responsive to higher *GDs* (elasticity = 1.85), followed by corn (0.96), alfalfa (0.49) and spring wheat (0.37). On the other hand, spring wheat is found to suffer most yield losses from marginally higher *SDs* (-0.37), followed by corn (-0.17), alfalfa (-0.13) and soy (-0.11). We have argued that imbalances in yield impacts due to weather may lead to farmer adaptations through the crop choices that are most profitable. Historically, the growing season length has increased, thus more *GDs*, and summer-time warming intensified, thus more *SDs*. The observed shift of production systems away from wheat, and towards corn and soybeans, is in line with how sensitive these crops are to such weather outcomes.

Table 9 presents the results of the IV-regressions used to estimate government payments. The government payments' estimates are then used in eq. (3). A higher expectation of the market prices for commodities results in higher crop insurance subsidies. Broadly, we find government payments to be most sensitive to *DRYZ* and *WETZ* predictions based on past realizations. We control for county-fixed effects as county demographics like age, experience, soil quality may affect the choice to buy crop insurance.

The estimation results for land-use shares among corn, soybeans and wheat are listed in Table 10. The explanatory variables of interest here are net per-acre crop returns due to trends and due to weather realizations during 1996-2013. In the case of corn, net returns from yield trends affect corn acreage positively while the impact of weather has been insignificant. For spring wheat, higher returns due to weather realizations are found to have increased its acreage. However, spring wheat's higher yield trends are found to disincentivize its acreage where corn's higher yield trends are found to produce a positive impact on its acreage. This result may be driven by the fact that post 1995 yield trends for spring wheat and corn are almost perfectly

correlated, see figure 6. For soybeans, higher yield trends are found to incentivize acreage but the case of weather-driven-net-returns is opposite. Rather, we find that higher weather-driven-net-returns for spring wheat incentivize soy acreage. The ambiguity may be due to overlapping growing seasons and temperature thresholds for these crops. Further, soybeans are rotated with corn as well as spring wheat and we do not capture such effects in our models yet. To that extent these results are preliminary.

Discussion

Many studies have analyzed the vulnerability of the agricultural sector to climate change. Temperature and moisture are critical components of a plant's growth cycle. Hence, short-term fluctuations as well as long-term changes in weather outcomes are bound to impact agricultural productivity. In the U.S., researchers have extensively studied the climate impact of corn yield as it is critical to the country's food, feed and biofuels industry, as well as its exports. Other commodities have received lesser attention in the literature. This paper develops an integrated yield modelling framework that analyzes all major crops in a region, and further evaluates their comparative compatibility to the region's weather and soils. The motivation to extend yield models to lesser-studied crops is the peculiarity of the region under study: the states of North and South Dakota of the U.S. Northern Great Plains. This region has experienced rapid land-use changes characterized by a shift of agricultural production system to corn and soybean cultivation, and away from wheat and grasses. This is the first study, to our best knowledge, to have utilized a comparative yield modelling framework to understand the role of climate on regional land-use change.

Among the land-use types analyzed in this study, alfalfa is a particularly interesting case. Alfalfa is primarily used as animal feed, and so we consider it as proxy for region's native

grasses. We combine the existing yield modelling strategies to establish thresholds-based non-linear, concave yield-weather relationship for each crops. We also extend the pre-existing yields models by introducing flexible trends, trend-weather interactions and soil-weather interactions as explanatory variables. Our findings provide insights into the role of weather/climate in recent land use change across the Great Plains.

Corn is known to be a disproportionate beneficiary of the historical R&D efforts to develop better, sturdier seed varieties. This fact supports our analysis of relative trends where corn yields have grown faster than other crop. An implication is that policy-makers can improve long-term yields by encouraging appropriate R&D incentives and ensuring high adoption rates. However, if trends were a surrogate for R&D activity then our finding that trend-weather interaction terms were non-positive means that higher R&D investments have not resulted in negating the adverse impacts of climate stressors. This has implications for future food production since the intensity and frequency of climate stressors through high heat, droughts and/or floods are predicted to intensify. The soil-weather interactions reveal that soil-limitations potentially worsen the impact of extreme weather events. This may lead to an overall reduction in availability of land that supports high yields as climate stressors intensify in future, ultimately stressing food supply. Also, the demand for good land would increase thereby leading to higher land prices and costlier commodities. Our finding that consecutive hot days are more harmful than isolated events also bears negative implications for all crops, as temperature rises and extreme heat events become more frequent due to climate change.

We assess how competitive the region's main crops will be under climate change. We find that corn and soybean have become more competitive due to historical climate change. From here we can conclude that if growing seasons expand and summer temperatures intensify in

future, then corn and soybeans will continue to enjoy an agronomic advantage in this region. However, our land-use regressions do not suggest a definitive role of short-term weather realizations in explaining shares, although ours is a work in progress.

Our work points to the need for yield models that better articulate interactions between soil quality and weather. Our findings have implications for crop-based and livestock-based agricultural systems. Further, by addressing land-use switches away from the regional grasses this study may garner interests among conservations enthusiasts and those interested in related ecosystem services from the Great Plains, as well as to scientists interested in how climate change affects food production.

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TABLES

Table 1: Palmer Z's characterization of wetness and droughts

Category	Palmer Z
Extreme Wetness	≥ 3.50
Severe Wetness	[2.50, 3.49]
Mild to Moderate Wetness	[1.00, 2.49]
Near Normal	[-1.24, 0.99]
Mild to Moderate Drought	[-1.99, -1.25]
Severe Drought	[-2.74, -2.00]
Extreme Drought	≤ -2.75

Table 2: Growing seasons and temperature thresholds for corn, soybean, spring wheat and alfalfa

Commodity	Growing Season	Temperature Thresholds
CORN	May-August	$GD \in [7^{\circ}C, 28^{\circ}C]; SD \geq 32^{\circ}C$
SOYBEANS	May-August	$GD \in [3^{\circ}C, 26^{\circ}C]; SD \geq 32^{\circ}C$
SPRING WHEAT	April-July	$GD \in [6^{\circ}C, 20^{\circ}C]; SD \geq 25^{\circ}C$
ALFALFA	April-July	$GD \in [10^{\circ}C, 27^{\circ}C]; SD \geq 30^{\circ}C$

Table 3: Decadal summaries of monthly weather variables.

Variable	1950-'60	1961-'70	1971-'80	1981-'90	1990-'00	2001-'10
CORN						
<i>GD</i>	2485.43	2522.64	2578.14	2524.00	2457.44	2501.56
<i>SD</i>	44.29	44.11	51.84	43.401	20.14	35.96
<i>DRYZ</i>	0.60	0.36	1.022	1.09	0.18	0.66
<i>WETZ</i>	0.84	1.52	0.79	0.78	2.48	1.61
SOYBEANS						
<i>GD</i>	3345.14	3338.83	3396.36	3317.19	3255.34	3247.07
<i>SD</i>	43.19	38.90	46.25	42.718	19.13	30.99
<i>DRYZ</i>	0.42	0.28	1.00	1.23	0.13	0.56
<i>WETZ</i>	0.68	1.50	0.76	0.70	2.39	1.73
SPRING WHEAT						
<i>GD</i>	1527.24	1544.72	1588.16	1586.22	1516.72	1554.51
<i>SD</i>	225.03	221.06	248.03	229.09	147.64	199.79
<i>DRYZ</i>	0.64	0.25	1.06	1.30	0.16	0.68
<i>WETZ</i>	0.63	1.56	0.86	1.07	2.45	1.40
ALFALFA						
<i>GD</i>	1445.93	1457.28	1458.50	1376.34	1362.88	1458.49
<i>SD</i>	59.87	56.39	56.41	43.31	27.29	52.55
<i>DRYZ</i>	0.64	0.25	0.96	1.61	0.13	0.67
<i>WETZ</i>	0.63	1.56	1.01	0.78	2.04	1.51

Table 4: The (parsimonious) yields regression model. Dependent Variables: Yields (bu./ac.)

	CORN	SOYBEAN	SPRING WHEAT	ALFALFA
Variable	Estimate	Estimate	Estimate	Estimate
<i>Intercept</i>	28.792***	21.712***	29.119***	0.779***
<i>t</i>	0.858***	0.229***	0.757***	-0.002
<i>t65</i>	0.873***	0.328***	-0.405***	0.037***
<i>t80</i>	-0.823***	-0.232***	-0.298***	-0.034***
<i>t95</i>	1.334***	0.130***	0.779***	0.014***
<i>GD</i>	0.023***	0.012***	0.007***	0.001***
<i>t</i> × <i>GD</i>	0.001***	0.002***	0.001***	0.001***
<i>SD</i>	-0.250***	-0.070***	-0.048***	-0.004***
<i>t</i> × <i>SD</i>	-0.010***	-0.002***	-0.001***	-0.0002***
<i>DRYZ</i>	-3.286***	-1.150***	-1.008***	-0.162***
<i>t</i> × <i>DRYZ</i>	-0.044***	0.011**	-0.011***	-0.002***
<i>DRYZ</i> × <i>SD</i>	0.035***	0.006***	-0.0003	0.001***
<i>WETZ</i>	0.048	0.275***	-0.520***	0.065***
<i>t</i> × <i>WETZ</i>	-0.025***	-0.006***	-0.011***	-0.0003**
<i>WETZ</i> × <i>SD</i>	0.026***	0.020***	0.0003	0.001***
% <i>lcc234</i> [<i>S</i>]× <i>SD</i>	-0.004***	-0.0001	-0.0001	-0.0001**
% <i>lcc234</i> [<i>S</i>]× <i>DRYZ</i>	-0.017	0.010	-0.007	-0.001
% <i>lcc234</i> [<i>W</i>]× <i>WETZ</i>	-0.001	-0.006	-0.034***	-0.001***
<i>R</i> ²	0.8254	0.8192	0.7616	0.7817
<i>N</i>	6,989	2,911	7,112	6,165

****p*<0.01, ***p*<0.05, **p*>0.1

Table 5: Isolated vs. Consecutive SDDs

	CORN	SOYBEAN	SPRING WHEAT	ALFALFA
Variable	Estimate	Estimate	Estimate	Estimate
<i>Intercept</i>	29.565***	22.544***	29.346***	0.774***
<i>t</i>	0.887***	0.257***	0.765***	-0.002
<i>t65</i>	0.837***	0.311***	-0.434***	0.037***
<i>t80</i>	-0.831***	-0.239***	-0.290***	-0.034***
<i>t95</i>	1.352***	0.139***	0.818***	0.016***
<i>GD</i>	0.023***	0.012***	0.006***	0.001***
<i>t</i> × <i>GD</i>	0.001***	0.002***	0.001***	0.001***
<i>SDD1</i>	-0.125**	0.052*	0.094***	-0.008***
<i>t</i> × <i>SDD1</i>	-0.016***	0.002	0.0005	-0.001***
<i>SDD23</i>	-0.864***	-0.181***	-0.007	-0.018***
<i>t</i> × <i>SDD23</i>	-0.038***	-0.005***	-0.0003	-0.001***
<i>SDD4+</i>	-1.207***	-0.217***	-1.346***	-0.019***
<i>t</i> × <i>SDD4+</i>	-0.046***	-0.006***	-0.026***	-0.001***
<i>DRYZ</i>	-3.307***	-1.200***	-1.110***	-0.155***
<i>t</i> × <i>DRYZ</i>	-0.043***	0.011*	-0.014***	-0.002***
<i>DRYZ</i> × <i>SD</i>	0.035***	0.008***	0.0004	0.001***

<i>WETZ</i>	0.072	0.264***	-0.511***	0.069***
<i>t</i> × <i>WETZ</i>	-0.026***	-0.006**	-0.011***	-0.0003**
<i>WETZ</i> × <i>SD</i>	0.026***	0.020***	0.0004	0.001***
<i>%lcc234[S]</i> × <i>SD</i>	-0.004***	-0.0001	-0.0001	-0.0001**
<i>%lcc234[S]</i> × <i>DRYZ</i>	-0.016	0.007	-0.006	-0.001
<i>%lcc234[W]</i> × <i>WETZ</i>	-0.0002	-0.006	-0.036***	-0.001***
R²	0.8264	0.8220	0.7688	0.7834
N	6,989	2,911	7,112	6,165

*** $p < 0.01$, ** $p < 0.05$, * $p > 0.1$

Table 6: Seasonal Weather Impacts: Corn and Soybeans

Growing Season: May-August		CORN	SOYBEAN
Variable		Estimate	Estimate
<i>Intercept</i>		30.416***	21.146***
<i>t</i>		0.942***	0.220***
<i>t65</i>		0.785***	0.368***
<i>t80</i>		-0.874***	-0.342***
<i>t95</i>		1.670***	0.359***
<i>GD_MAY_JUN</i>		0.022***	0.012***
<i>t</i> × <i>GD_MAY_JUN</i>		0.002***	0.001***
<i>GD_JUL_AUG</i>		0.023***	0.017***
<i>t</i> × <i>GD_JUL_AUG</i>		0.0004***	-0.006***
<i>SD_MAY_JUN</i>		0.075	0.094***
<i>t</i> × <i>SD_MAY_JUN</i>		0.002	0.001*
<i>SD_JUL_AUG</i>		-0.285***	-0.091***
<i>t</i> × <i>SD_JUL_AUG</i>		-0.011***	-0.002***
<i>DRYZ_MAY_JUN</i>		-1.933***	-1.033***
<i>t</i> × <i>DRYZ_MAY_JUN</i>		-0.092***	-0.001
<i>DRYZ</i> × <i>SD_MAY_JUN</i>		0.004	-0.023***
<i>DRYZ_JUL_AUG</i>		-5.120***	-1.329***
<i>t</i> × <i>DRYZ_JUL_AUG</i>		-0.041**	-0.020**
<i>DRYZ</i> × <i>SD_JUL_AUG</i>		0.045***	0.009***
<i>WETZ_MAY_JUN</i>		-0.803***	-0.075
<i>t</i> × <i>WETZ_MAY_JUN</i>		-0.011	-0.003
<i>WETZ</i> × <i>SD_MAY_JUN</i>		-0.080	0.066***
<i>WETZ_JUL_AUG</i>		0.697***	0.898***
<i>t</i> × <i>WETZ_JUL_AUG</i>		-0.035***	-0.013***
<i>WETZ</i> × <i>SD_JUL_AUG</i>		0.054***	0.039***
<i>%lcc234[S]</i> × <i>SD</i>		-0.004***	-0.000002
<i>%lcc234[S]</i> × <i>DRYZ</i>		0.003	0.004
<i>%lcc234[W]</i> × <i>WETZ</i>		-0.005	-0.005
R²		0.8326	0.8398
N		6,989	2,911

*** $p < 0.01$, ** $p < 0.05$, * $p > 0.1$

Table 7: Seasonal Weather Impacts: Spring Wheat and Alfalfa

Growing Season: April-July	SPRING WHEAT	ALFALFA
Variable	Estimate	Estimate
<i>Intercept</i>	29.692***	0.839***
<i>t</i>	0.823***	0.002
<i>t65</i>	-0.497***	0.031***
<i>t80</i>	-0.233***	-0.030***
<i>t95</i>	0.784***	0.008***
<i>GD_APR_MAY</i>	0.010***	0.0002***
<i>t</i> × <i>GD_APR_MAY</i>	0.0002**	0.00003***
<i>GD_JUN_JUL</i>	-0.015***	0.001***
<i>t</i> × <i>GD_JUN_JUL</i>	0.001***	0.001***
<i>SD_APR_MAY</i>	0.018***	-0.006***
<i>t</i> × <i>SD_APR_MAY</i>	0.003***	0.0003***
<i>SD_JUN_JUL</i>	-0.040***	-0.005***
<i>t</i> × <i>SD_JUN_JUL</i>	-0.002***	-0.0002***
<i>DRYZ_APR_MAY</i>	-1.508***	-0.121***
<i>t</i> × <i>DRYZ_APR_MAY</i>	-0.054***	-0.004***
<i>DRYZ</i> × <i>SD_APR_MAY</i>	-0.011***	0.002**
<i>DRYZ_JUN_JUL</i>	-1.342***	-0.185***
<i>t</i> × <i>DRYZ_JUN_JUL</i>	0.020***	-0.0003
<i>DRYZ</i> × <i>SD_JUN_JUL</i>	0.0002	0.001***
<i>WETZ_APR_MAY</i>	-0.056	0.059***
<i>t</i> × <i>WETZ_APR_MAY</i>	-0.008**	-0.001***
<i>WETZ</i> × <i>SD_APR_MAY</i>	-0.009**	0.003
<i>WETZ_JUN_JUL</i>	-0.507***	0.055***
<i>t</i> × <i>WETZ_JUN_JUL</i>	-0.020***	-0.0003*
<i>WETZ</i> × <i>SD_JUN_JUL</i>	0.001	0.001***
% <i>lcc234[S]</i> × <i>SD</i>	-0.0001	-0.0001***
% <i>lcc234[S]</i> × <i>DRYZ</i>	-0.004	-0.001
% <i>lcc234[W]</i> × <i>WETZ</i>	-0.034***	-0.001***
R²	0.7898	0.7892
N	7,112	6,165

*** $p < 0.01$, ** $p < 0.05$, * $p > 0.1$

Table 8: Yields-weather elasticities (Crop Competitiveness)

Variable	CORN (59 bu./ac.)	SOYBEANS (22 bu./ac.)	SPRING WHEAT (27 bu./ac.)	ALFALFA (55 bu/ac)
<i>GD</i>	0.9595	1.8465	0.3740	0.49138
<i>KDD</i>	-0.1692	-0.1106	-0.3732	-0.1283
<i>DRYZ</i>	-0.0368	-0.0319	-0.0250	-0.0617
<i>WETZ</i>	0.0011	0.0180	-0.0256	0.0514

Table 9: IV Regressions for Government Payments Variables

Regressors	Crop Insurance Subsidy			Disaster Payments	Farm Subsidies
	Corn	Soybeans	Wheat		
Intercept	4.10*	-11.61	18.34***	198.82***	8.64***
Trends				0.48***	
Corn Price	0.77***				
Soy Price		0.41***			
Wheat Price			0.34***		
Average Price					-0.21***
<i>GD</i>	0.001	-0.003	-0.004***	-0.09***	0.003***
<i>SD</i>	0.004	0.04**	0.002	0.46***	-0.01***
<i>DRYZ</i>	0.25**	0.14	0.54***	-1.8	0.02
<i>WETZ</i>	0.41***	0.24	0.16***	-0.08	0.22***
Fixed Effects	Yes	Yes	Yes	Yes	Yes
R ²	0.84	0.82	0.91	0.20	0.82

*** $p < 0.01$, ** $p < 0.05$, * $p > 0.1$

Table 10: Land-Use Transition Models Due to Per Acre Crop Profits: The SUR Model.

	CORN	SOYBEAN	SPRING WHEAT
Regressors	Estimate	Estimate	Estimate
Per Acre Profits- due to trends			
$\pi^{CORN} f(t)$	0.005***	0.010***	0.003**
$\pi^{SOY} f(t)$	0.019***	0.021***	0.000
$\pi^{SPRING WHEAT} f(t)$	-0.005***	-0.003*	-0.002*
Per Acre Profits- due to weather (& soils)			
$\pi^{CORN} W, S$	0.0001	-0.002	-0.004**
$\pi^{SOY} W, S$	-0.019***	-0.024***	0.002
$\pi^{SPRING WHEAT} W, S$	0.009***	0.008***	0.010***
Crop Insurance Subsidy			
Corn	-0.487***	-0.888***	-0.182*
Soybeans	-0.012	-0.282**	0.013
Wheat	0.024	0.196	0.207**
Other Govt. Payments			
Disaster Payments	0.072***	0.200***	0.031
Farm Subsidies	3.970***	3.939***	1.315**
Fixed Effects	Yes	Yes	Yes
System Weighted R ²	0.98		

*** $p < 0.01$, ** $p < 0.05$, * $p > 0.1$

FIGURES

Figure 1: Historical Yield Trends for corn, alfalfa, soy and sp. wheat, standardized at 1950 = 1.

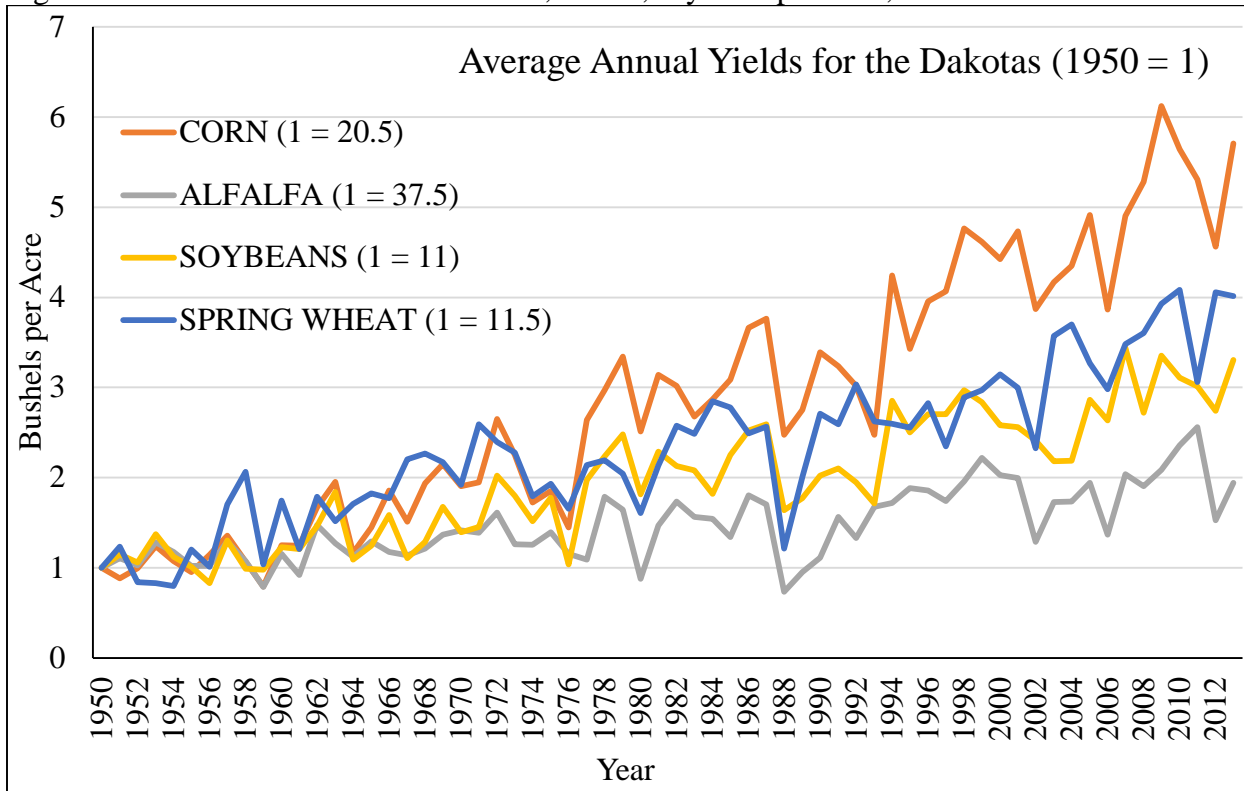


Figure 2: Corn Yields vs. Number of Days in Each Degree-Celsius Bin

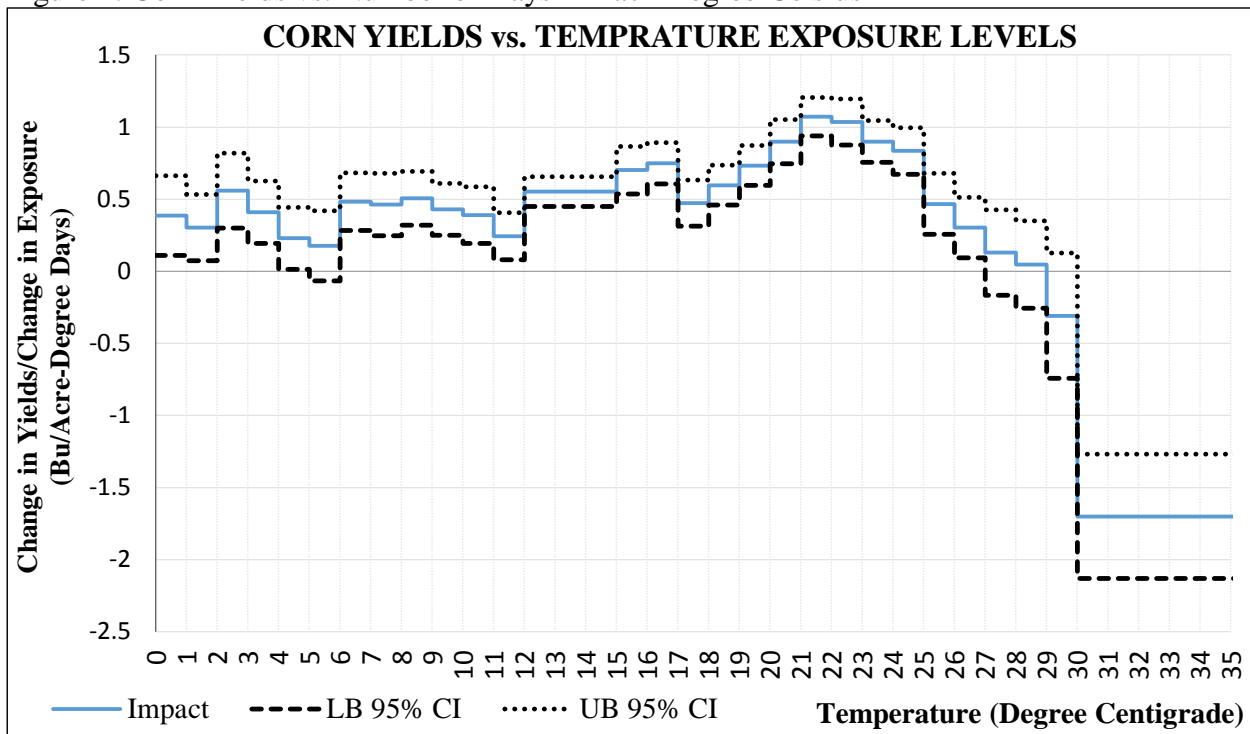


Figure 3: Spring Wheat Yields vs. Number of Days in Each Degree-Celsius Bin

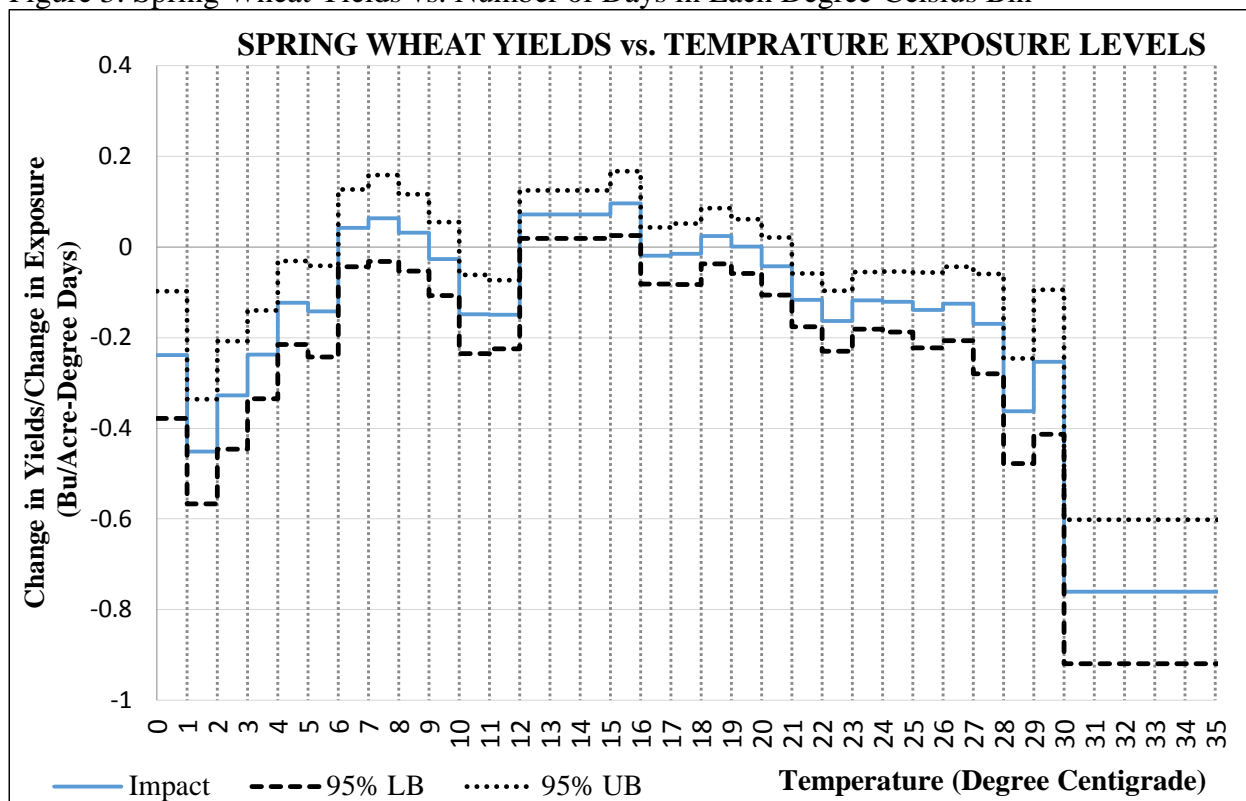


Figure 4: Alfalfa Yields vs. Number of Days in Each Degree-Celsius Bin

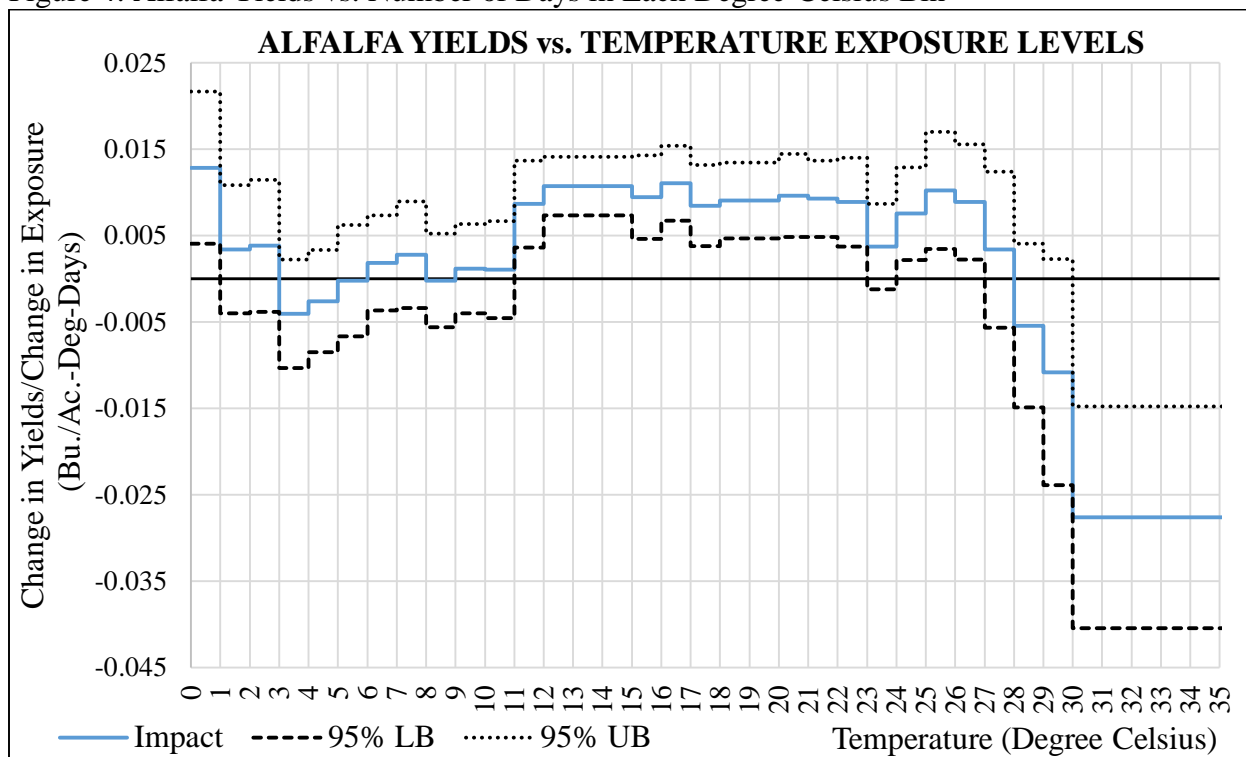


Figure 5: Soybean Yields vs. Number of Days in Each Degree-Celsius Bin

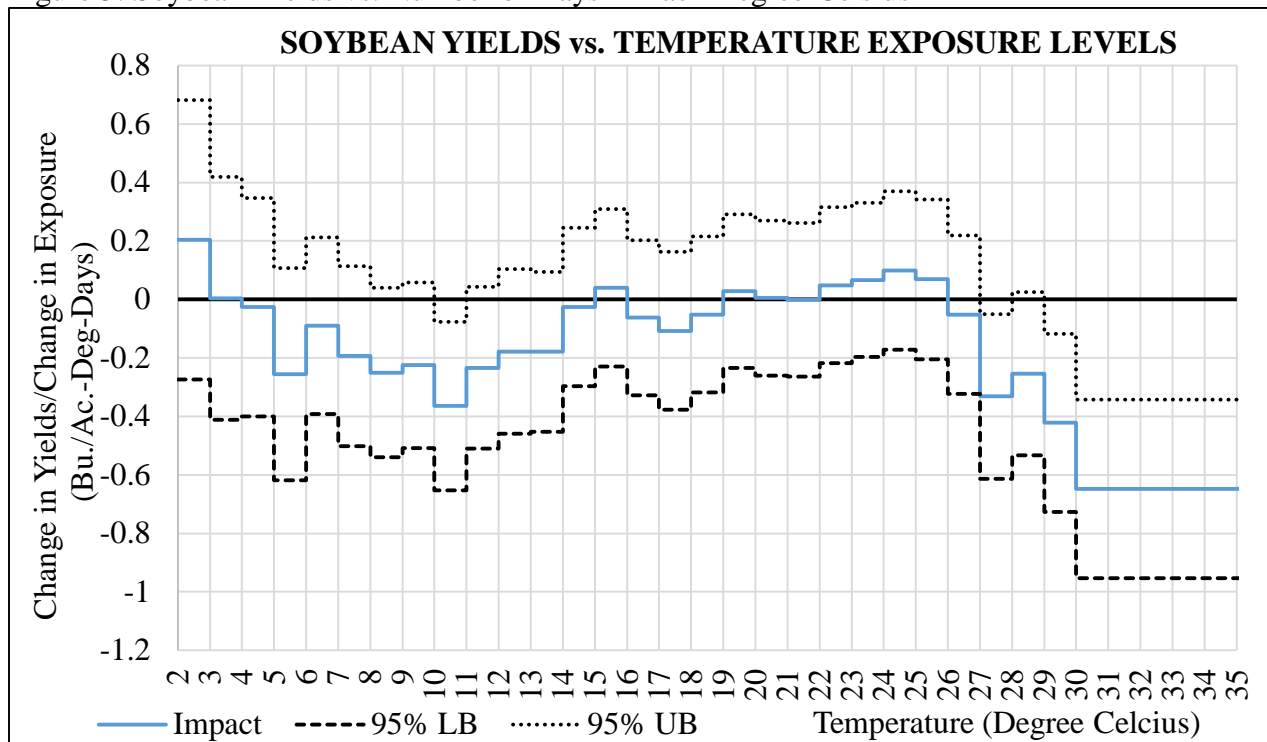


Figure 6: Marginal Trend Impacts of Crop Yields. The starting values in 1950 are standardized to equal 1.

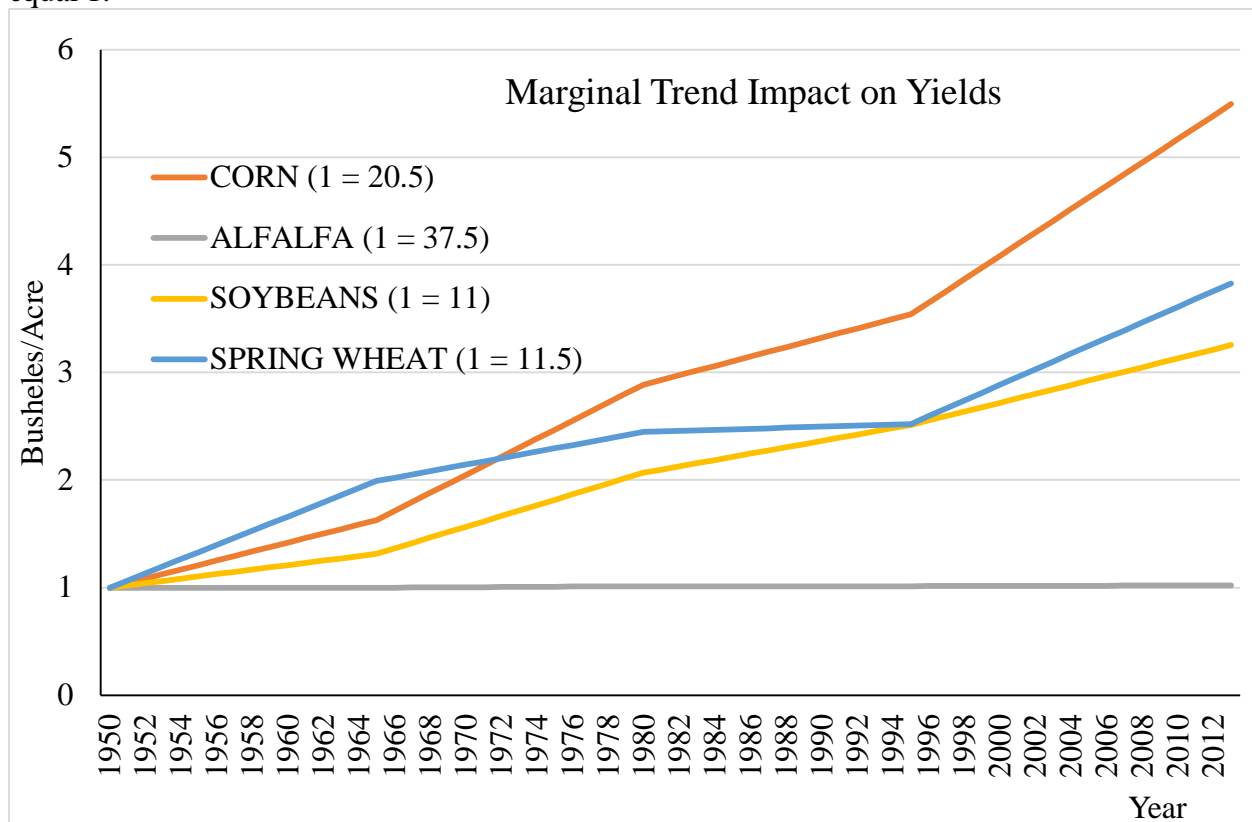
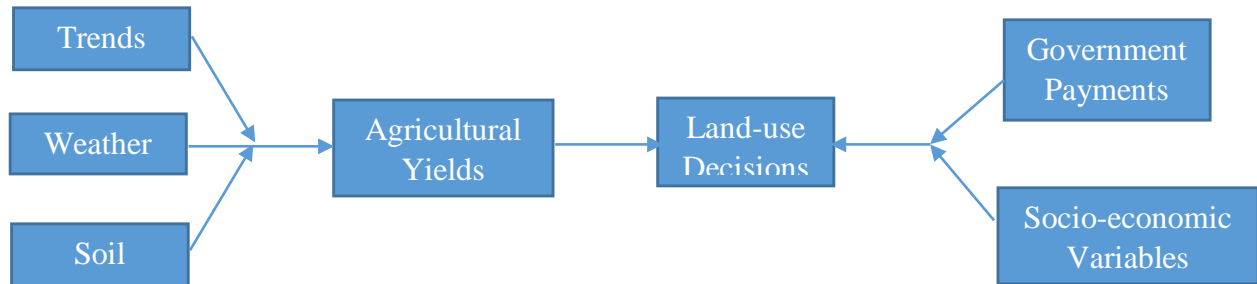


Figure 7: Land-Use Switching: Conceptual Framework.



APPENDIX

Crop Yields and Historical Weather Outcomes

SD Categorization

Consider a snapshot of a representative county i 's yields at year t . We know from our econometric estimations that this county's yields would increase given an additional GD and decrease given an additional SD .

We now want to evaluate the impact of an additional SD if it occurred as an isolated single-day event or for 2 or more consecutive days. In other words, we divide the total bag of heat accumulated in SD s into various categories and want to test whether an additional unit of SD in one category is more harmful than in the other category.

For a mathematical representation of this hypothesis, consider a simplified (hypothetical) situation where SD s are accumulated only as isolated single-day events or as consecutive 2-day events in year t . Let $I(1)$ be the total frequency of single-day heat events and $I(2)$ be the total frequency of 2-day heat events during the year t growing season. Therefore, the total number of days when $SD > 0$ equals $I(1) + 2I(2)$. Also, let m_1 and m_2 represent average heat accumulated per day in the single-day and the consecutive 2-day categories respectively. So,

$$m_1 = \frac{\sum_{d \in I(1)} (T_d - 32)}{I(1)}, \text{ and}$$
$$m_2 = \frac{\sum_{d \in I(2)} (T_d - 32)}{2I(2)}. \quad (\because 2I(2) \text{ is the total number of days in this category})$$

So, we can express total heat accumulated under the isolated single-day category ($SDD1$) and the consecutive 2-day category ($SDD2$) as:

$$SDD1 = m_1 I(1)$$

$$SDD2 = 2m_2 I(2)$$

In the yield regression model for county i for year t we have

$$Y = \beta_0 + \beta_1 SDD1 + \beta_2 SDD2 + \text{other controls..}$$

$$= \beta_0 + \beta_1 m_1 I(1) + 2\beta_2 m_2 I(2) + ..$$

In this regression framework, the **quantum of heat** among $SDD1$ and $SDD2$ categories can potentially differ across three dimensions: **1)** average per day heat (m_1 vs. m_2); **2)** frequency of the event ($I(1)$ vs. $I(2)$); and **3)** because two single-day events are essentially bundled up into one consecutive 2-day event. Now, if $m_2 = k_m m_1$ and $I(2) = k_I I(1)$ then we can re-write the regression equation above as follows:

$$Y = \beta_0 + \beta_1 m_1 I(1) + 2k_m k_I \beta_2 m_1 I(1) + ..$$

$$= \beta_0 + \beta_1 SDD1 + 2k_m k_I \beta_2 SDD1 + ..$$

The above regression is essentially a **structural** breakdown of $SDDs$ because it compares the impact of an additional unit of $SDD1$ on yields in isolation and in two consecutive repetitions.

Since $SDD1$ is the common denominator of marginal response of yields, the coefficients β_1 and $2k_m k_I \beta_2$ are directly comparable. An alternative way to achieve this is to divide $SDD2$ by $2k_m k_I$.

It is important to realize that the factor $2k_m k_I$ captures disproportionate heat intensity across SD categories. $SDDs$ with higher continuity are observed to be much less frequent, but at the same time they could accumulate higher *or* lower mean heat per day (m). This is a purely empirical issue and a fixed standardizing factor of 2 for $SDD2$ or 3 for $SDD3$ may not be perfect.

Where do the (spatio-temporal) means of different SD categories fit into the above framework?

The means of SD^l s, SD^{23} s and SD^{4+} s are basically a proxy for $2k_mk_l$. The reason they are only an approximation is that the above framework applies only to a snapshot of a particular county in a particular year. Each county will have a different value $2k_mk_l$ that may differ across different years. Ideally, one should use a standardization factor that varies with county and year, but then the interpretation of the resulting variable will not be as straightforward. Therefore, an overall mean is a plausible candidate for normalization.

Robustness (Estimation Results, Yield-Weather Models): We conduct robustness tests on our corn yield model estimates. For this purpose, we either break that spatially into: north vs. south and east vs. west, or we utilize weighted regressions with average crop-acreage share for each county as weights.

A. *East of the 100th Meridian vs. West of the 100th Meridian* (see Table A1-A2): 100th meridian cuts the U.S. mainland into two type of agricultural land, i.e. the eastern half is generally rain-fed and the west needs irrigation for growing crops. Now the 100th meridian cuts the Dakotas into halves and thus the western portion of the states is really at the non-irrigated/irrigated margin considering the total east-west expanse of the United States. However, if the western Dakotas are significantly irrigated then the impact of dry seasons and/or SD s may be undermined in our regressions. This is why these robustness test are important. We find our estimates to be robust.

B. *North Dakota vs. South Dakota* (see Table A3-A4): South Dakota is warmer than its northern counterpart and may be better for agriculture through richer spatio-temporal yields data driving the results. However, we find our model estimates to be robust.

C. *Weighted Regressions* (Table A5): Since the respondent density is affected by crop failures, county-level yield estimates reposted by NASS are also prone to measurement errors. This issue is dealt with using weighted least squares regressions where the weights are various functional variations of county-level crop acreage shares. Weights may be time-invariant in this study. Only trends and trend-weather interactions are problematic, rest are robust. The issue with trends arises due to the loss of monotonicity when multiplied by non-monotonic weights.

Annual Weather Realizations, Crop Competitiveness and Land-Use Change

Weather Outcome Predictions: Econometric Considerations and Results

Consider an AR(4) (panel) time-series process for the GDD s with $E(GDD_{i,t}) = \gamma_i + \gamma_t t$:

$$GDD_{i,t} = \gamma_t^* t + \sum_{k=1}^4 \gamma_k GDD_{i,t-k} + (1 - \sum_{k=1}^4 \gamma_k) \gamma_i + v_{i,t}, \quad (\text{A.1})$$

where $v_{i,t}$ is assumed to be a white noise process, γ_i represents county-level means (fixed-effects), $\gamma_t^* = (1 - \sum_{k=1}^4 \gamma_k) \gamma_t$, and thus $E(GDD_{i,t}) = \gamma_i + \gamma_t t$. $GDD_{i,t}$ must be stationary in order for the above process to be estimable. The counterpart of stationarity of an autoregressive process is its invertibility. So to test stationarity of our panel data series for weather we conduct unit-root tests for the AR process by following a procedure proposed by Breitung and Meyer (1994). The corresponding t-test relies upon transforming equation A.1 such that the test statistic for the null hypothesis of a unit root, i.e. $\sum_{k=1}^4 \gamma_k = 1$, is asymptotically normally distributed, also

termed as the “unbiased test-statistic”.¹¹ Specifically, Breitung and Meyer (1994) suggest the following transformation of (A.1) using the first value of the process $GDD_{i,0}$,

$$GDD_{i,t} - GDD_{i,0} = \gamma_t(1 - \sum_{k=1}^4 \gamma_k)t + \sum_{k=1}^4 \gamma_k(GDD_{i,t-k} - GDD_{i,0}) + v_{i,t} - (1 - \sum_{k=1}^4 \gamma_k)(GDD_{i,0} - \gamma_i) \quad (\text{A.2})$$

See that the impact of individual means vanishes under this transformation under the null,

$\sum_{k=1}^4 \gamma_k = 1$, making regular t-test viable. We implement Breitung and Meyer’s (1994) test

procedure for individual weather series ($GDD_{i,t}$, $SDD_{i,t}$, $DRYPZ_{i,t}$ and $WETPZ_{i,t}$) in SAS’s panel model procedure – “Unbiased (UB) Test”. Results are presented in tables A6-A8.

We find $GD_{i,t}$, $SD_{i,t}$ and $WETZ_{i,t}$ to be trend-stationary around count-level means for all three commodities, whereas $DRYZ_{i,t}$ is found to be non-stationary. An implication of this result is that severe to extreme droughts is too random an event to be predicted well. However, upon further investigation a subset of the $DRYZ_{i,t}$ data series, that matches up with the availability of yields data (temporally and county-wise), is found to be trend-stationary around county-level means for corn and spring wheat.¹² We utilize the stationary subset of $DRYZ$ s, although we assert a minor caveat with the predictions given our analysis relies on a particular stationarity test.

Predicting Yields: Decomposing the effects of Trends and Weather-Soil

¹¹ Data transformation is necessary since under the alternative hypothesis of stationarity the t-test is subject to loss of power due to individual means. Breitung and Meyer’s (1994) approach is similar to the Dickey-Fuller test of Fuller (1976), although the latter proposed a bias-corrected test-statistic with critical values differing from a normally distributed t-statistic.

¹² Corn’s $DRYZ$ predictions are also applicable to soybeans because these crops have similar growing seasons, and the counties that grow soybeans are only a subset of those that grow corn.

We utilize a fixed-effects panel regression to estimate the yield-weather relationship in equation (1). To be able to decompose the total predicted yields into component that are driven purely by trends and by weather (and soil) effects, we need to separate county fixed-effects as well. This is achieved by utilizing sample means from the data and estimating the following model:

$$Y_{i,t} = f(t) + \beta_W W_{i,t} + \beta_{SW} Q_i W_{i,t} + \sum_i \beta_{D,i} D_i + \eta_{i,t}, \quad (\text{A.3})$$

where D_i represents county dummy variables. Other variable notations and their definitions in (A.3) hold as per this document's main text.¹³ We utilize coefficient estimates from (A.3) and weather predictions from the AR(4) regressions above to evaluate decomposed yield estimates, $\hat{Y}_{i,t|f(t)}^l = \hat{f}(t)$ and $\hat{Y}_{i,t|\hat{W},S}^l = \hat{\beta}_W \hat{W}_{i,t} + \hat{\beta}_{SW} Q_i \hat{W}_{i,t}$, that are then used to calculate per-acre returns, $\pi_{i,t|f(t)}^l = P_t^l \hat{Y}_{i,t|f(t)}^l - C_t^l$ and $\pi_{i,t|\hat{W},Q}^l = P_t^l \hat{Y}_{i,t|\hat{W},Q}^l - C_t^l$, that enter the land-use shares model in equation (3). Note that $\hat{Y}_{i,t|f(t)}^l$ and $\hat{Y}_{i,t|\hat{W},Q}^l$ (as estimated) account for “change” due to trends and weather, and not “levels”. Yield level estimates are accounted for by the county-level means $\beta_{D,i}$.

Table A1: Variable Summaries for counties that are located east and west of the 100th Meridian.

Variable	East	West
<i>GD</i>	2573.20	2399.83
<i>SD</i>	33.78	46.56
<i>DRYZ</i>	0.59	0.75
<i>WETZ</i>	1.32	1.38
<i>%lcc234[S]</i>	10.15	6.68
<i>%lcc234[W]</i>	9.48	1.42

¹³ Note that we have assumed $\beta_{iW} = 0$ in (A.3). Other coefficient estimates are robust to this assumption with minor aberrations. We do not report these regression results to save space, but are available upon request.

Table A2: Corn yield models for counties that are located east and west of the 100th Meridian.

CORN	EAST	WEST
Variable	Estimate	Estimate
<i>Intercept</i>	61.014***	26.595***
<i>t</i>	0.929***	0.905***
<i>t65</i>	0.581***	1.040***
<i>t80</i>	-0.100	-1.738***
<i>t95</i>	1.246***	1.348***
<i>GD</i>	0.025***	0.015***
<i>t</i> × <i>GD</i>	0.001***	0.001***
<i>SD</i>	-0.334***	-0.111***
<i>t</i> × <i>SD</i>	-0.010***	-0.005***
<i>DRYZ</i>	-3.068***	-2.779***
<i>t</i> × <i>DRYZ</i>	-0.053***	-0.035**
<i>DRYZ</i> × <i>SD</i>	0.034***	0.027***
<i>WETZ</i>	-0.199	0.783***
<i>t</i> × <i>WETZ</i>	-0.037***	0.020**
<i>WETZ</i> × <i>SD</i>	0.039***	0.024***
% <i>lcc234</i> [<i>S</i>]× <i>SD</i>	-0.002*	-0.002
% <i>lcc234</i> [<i>S</i>]× <i>DRYZ</i>	-0.019	-0.003
% <i>lcc234</i> [<i>W</i>]× <i>WETZ</i>	-0.007	0.049
R²	0.8848	0.7071
N	3,899	2,305

*** $p < 0.01$, ** $p < 0.05$, * $p > 0.1$

Table A3: Variable Summaries for North and South Dakota counties.

Variable	North Dakota	South Dakota
<i>GD</i>	2337.44	2637.14
<i>SD</i>	22.37	52.33
<i>DRYZ</i>	0.78	0.58
<i>WETZ</i>	1.48	1.28
% <i>lcc234</i> [<i>S</i>]	7.23	9.99
% <i>lcc234</i> [<i>W</i>]	7.06	5.40

Table A4: Corn yield models for North and South Dakota counties.

CORN	NORTH DAKOTA	SOUTH DAKOTA
Variable	Estimate	Estimate
<i>Intercept</i>	44.270***	27.327***
<i>t</i>	0.829***	0.843***
<i>t65</i>	1.001***	0.879***
<i>t80</i>	-1.139***	-0.713***
<i>t95</i>	1.448***	1.295***
<i>GD</i>	0.030***	0.016***
<i>t</i> × <i>GD</i>	0.002***	0.001***
<i>SD</i>	-0.265***	-0.221***
<i>t</i> × <i>SD</i>	-0.009***	-0.010***
<i>DRYZ</i>	-3.679***	-4.425***
<i>t</i> × <i>DRYZ</i>	-0.096***	0.007
<i>DRYZ</i> × <i>SD</i>	0.047***	0.044***
<i>WETZ</i>	0.031	0.354
<i>t</i> × <i>WETZ</i>	-0.003	-0.043***
<i>WETZ</i> × <i>SD</i>	0.043***	0.031***
% <i>lcc234</i> [<i>S</i>] × <i>SD</i>	-0.0005	-0.005***
% <i>lcc234</i> [<i>S</i>] × <i>DRYZ</i>	0.009	0.039
% <i>lcc234</i> [<i>W</i>] × <i>WETZ</i>	-0.028**	0.044**
R²	0.8315	0.8282
N	2,907	4,082

*** $p < 0.01$, ** $p < 0.05$, * $p > 0.1$

Table A5: Weighted Regressions

CORN	WT	SQWT	SQMWT	WTBAR
Variable	Estimate	Estimate	Estimate	Estimate
<i>Intercept</i>	0.062	1.154	-0.092	2.191***
<i>t</i>	-0.690***	-0.363***	-0.467***	0.806***
<i>t65</i>	2.410***	2.275***	2.892***	0.662***
<i>t80</i>	-1.016***	-0.773***	-0.992***	-0.021
<i>t95</i>	1.968***	1.535***	-0.930***	1.259***
<i>GD</i>	0.008***	0.010***	-0.013***	0.015***
<i>t</i> × <i>GD</i>	-0.0005***	-0.00002	-0.0005***	-0.00002
<i>SD</i>	-0.245***	-0.246***	-0.264***	-0.290***
<i>t</i> × <i>SD</i>	-0.008***	-0.009***	0.010***	-0.010***
<i>DRYZ</i>	-5.336***	-4.373***	0.015***	-3.888***
<i>t</i> × <i>DRYZ</i>	0.039***	0.025**	0.006***	0.019*
<i>DRYZ</i> × <i>SD</i>	0.029***	0.031***	-0.002***	0.043***
<i>WETZ</i>	-0.146	-0.038	-0.004	-0.252*
<i>t</i> × <i>WETZ</i>	-0.038***	-0.037***	-0.004***	-0.035***
<i>WETZ</i> × <i>SD</i>	0.018***	0.025***	-0.001***	0.039***
% <i>lcc234</i> [<i>S</i>] × <i>SD</i>	-0.004***	-0.003***	-0.003***	-0.001
% <i>lcc234</i> [<i>S</i>] × <i>DRYZ</i>	0.070***	0.029	-0.031	0.039**
% <i>lcc234</i> [<i>W</i>] × <i>WETZ</i>	0.008	0.007	-0.016	0.021**
R²	0.9437	0.9339	0.9178	0.9574
N	6,989	6,989	6,989	6,989

*** $p < 0.01$, ** $p < 0.05$, * $p > 0.1$

Table A6: Unit Root Regressions for **Corn**'s seasonal Weather Outcomes. $H_o : \sum_{k=1}^4 \gamma_k = 1$

Regressors	<i>GD</i>	<i>SD</i>	<i>DRYZ</i>	<i>WETZ</i>
Trend	-1.09***	-0.37***	-0.061***	0.02***
$W_{i,t-1}$	0.25***	0.23***	-1.93***	-0.01
$W_{i,t-2}$	-0.22***	-0.11***	5.34***	0.12***
$W_{i,t-3}$	0.05***	0.02*	-2.22**	-0.05***
$W_{i,t-4}$	-0.05***	0.03**	-1.52***	-0.07***
Fixed-Effects	Yes	Yes	Yes	Yes
R ²	0.67	0.46	0.08	0.06
U.B. t-stat	-22.73***	-19.62***	57.09	-15.71***

*** $p < 0.01$, ** $p < 0.05$, * $p > 0.1$

Table A7: Unit Root Regressions for **Soybean**'s seasonal Weather Outcomes. $H_o : \sum_{k=1}^4 \gamma_k = 1$

Regressors	<i>GD</i>	<i>SD</i>	<i>DRYZ</i>	<i>WETZ</i>
Trend	-0.58	-0.40***	-0.061***	0.02***
$W_{i,t-1}$	0.26***	0.22***	-1.93***	-0.01
$W_{i,t-2}$	-0.19***	-0.11***	5.34***	0.12***
$W_{i,t-3}$	0.04***	0.02	-2.22**	-0.05***
$W_{i,t-4}$	-0.05***	0.03**	-1.52***	-0.07***
Fixed-Effects	Yes	Yes	Yes	Yes
R ²	0.69	0.46	0.08	0.06
U.B. t-stat	-22.91***	-19.57***	57.09	-15.71***

*** $p < 0.01$, ** $p < 0.05$, * $p > 0.1$

Table A8: Unit root regressions for **Spring Wheat**'s weather outcomes. $H_o : \sum_{k=1}^4 \gamma_k = 1$

Regressors	<i>GD</i>	<i>SD</i>	<i>DRYZ</i>	<i>WETZ</i>
Trend	0.09	-1.55***	-0.061***	0.02***
$W_{i,t-1}$	0.24***	0.22***	-1.93***	-0.01
$W_{i,t-2}$	-0.15***	-0.10***	5.34***	0.12***
$W_{i,t-3}$	0.007	0.02*	-2.22**	-0.05***
$W_{i,t-4}$	-0.02**	0.04***	-1.52***	-0.07***
Fixed-Effects	Yes	Yes	Yes	Yes
R ²	0.64	0.53	0.08	0.06
U.B. t-stat	-20.39***	-18.46***	57.09	-15.71***

*** $p < 0.01$, ** $p < 0.05$, * $p > 0.1$

Notes: Regressors $W_{i,t-k}$, $k \in \{1, 2, 3, 4\}$ denote lagged variables corresponding to only the dependent variable in each case.

Table A9: Yield-Weather Subset unit root regressions for DRYZ

Regressors	Corn/Soybeans (May – August)	Spring Wheat (April – July)
Trend	-0.001	-0.0004
$DRYZ_{i,t-1}$	0.06	0.13***
$DRYZ_{i,t-2}$	-0.06	-0.10***
$DRYZ_{i,t-3}$	0.03	0.03**
$DRYZ_{i,t-4}$	0.04	0.06***
Fixed-Effects	Yes	Yes
R^2	0.02	0.04
U.B. statistic	-	-15.39***
t-statistic	1418.40***	1383.20***

*** $p < 0.01$, ** $p < 0.05$, * $p > 0.1$

Table A10: Models for Corn's Seasonal Weather Outcomes

Regressors	$GD_{i,t}$	$SD_{i,t}$	$DRYZ_{i,t}$	$WETZ_{i,t}$
Trend	-0.96***	-0.31***	0.002	0.02***
$GD_{i,t-1}$	0.25***	0.02***	0.001***	-0.004***
$GD_{i,t-2}$	-0.20***	-0.02***	-0.001***	0.002***
$GD_{i,t-3}$	0.01	-0.01***	-0.001***	-0.001***
$GD_{i,t-4}$	-0.04***	0.01***	0.001***	-0.0002
$SD_{i,t-1}$	0.24***	0.26***	0.004***	-0.01***
$SD_{i,t-2}$	-0.06	-0.02	0.001	0.002
$SD_{i,t-3}$	0.12	-0.01	-0.002**	-0.003**
$SD_{i,t-4}$	0.10	0.03	-0.002**	0.01***
$DRYZ_{i,t-1}$	-1.01	-3.20***	-0.04***	0.12***
$DRYZ_{i,t-2}$	-2.27	-1.90***	-0.03**	-0.12***
$DRYZ_{i,t-3}$	2.23	0.47	0.06***	-0.06***
$DRYZ_{i,t-4}$	-6.33***	-1.11***	0.05***	0.04
$WETZ_{i,t-1}$	4.12***	-0.23	-0.07	-0.07***

$WETZ_{i,t-2}$	-0.70	-0.43**	-0.04***	0.14***
$WETZ_{i,t-3}$	-3.67***	-1.51***	-0.08***	-0.07***
$WETZ_{i,t-4}$	0.18	0.94***	0.04***	-0.07***
Fixed-Effects	Yes	Yes	Yes	Yes
R ²	0.68	0.57	0.08	0.14
N	7,259	7,259	6,513	7,259

*** $p < 0.01$, ** $p < 0.05$, * $p > 0.1$

Table A11: Models for Soybean's Seasonal Weather Outcomes

Regressors	$GD_{i,t}$	$SD_{i,t}$	$DRYZ_{i,t}$	$WETZ_{i,t}$
Trend	-0.48***	-0.33***	0.002	0.02***
$GD_{i,t-1}$	0.25***	0.02***	0.001***	-0.004***
$GD_{i,t-2}$	-0.16***	-0.02***	-0.001***	0.002***
$GD_{i,t-3}$	0.02	-0.01*	-0.001***	-0.001***
$GD_{i,t-4}$	-0.06***	0.01***	0.001***	-0.0001
$SD_{i,t-1}$	0.05	0.27***	0.004***	-0.01***
$SD_{i,t-2}$	-0.11	-0.02	0.001	0.002
$SD_{i,t-3}$	0.09	-0.03	-0.002**	-0.002*
$SD_{i,t-4}$	0.18**	0.04***	-0.002**	0.004***
$DRYZ_{i,t-1}$	3.77***	-3.38***	-0.04***	0.10***
$DRYZ_{i,t-2}$	-3.62**	-2.20***	-0.03**	-0.10***
$DRYZ_{i,t-3}$	1.90	0.60*	0.06***	-0.07***
$DRYZ_{i,t-4}$	-6.03***	-1.14***	0.05***	0.04*
$WETZ_{i,t-1}$	3.43***	-0.28	-0.07	-0.06***
$WETZ_{i,t-2}$	0.13	-0.33*	-0.04***	0.13***
$WETZ_{i,t-3}$	-3.52***	-1.63***	-0.08***	-0.07***
$WETZ_{i,t-4}$	-1.11	0.88***	0.04***	-0.07***
Fixed-Effects	Yes	Yes	Yes	Yes
R ²	0.69	0.49	0.08	0.14
N	7,259	7,259	6,513	7,259

*** $p < 0.01$, ** $p < 0.05$, * $p > 0.1$

Table A12 : Models for Spring Wheat's Seasonal Weather Outcomes

Regressors	$GD_{i,t}$	$SD_{i,t}$	$DRYZ_{i,t}$	$WETZ_{i,t}$
Trend	0.01	-1.12***	0.003**	0.02***
$GD_{i,t-1}$	0.30***	0.14***	0.002***	-0.01***
$GD_{i,t-2}$	-0.15***	-0.28***	-0.001***	0.01***
$GD_{i,t-3}$	0.04**	-0.02	0.002***	-0.003***
$GD_{i,t-4}$	-0.07***	-0.02	-0.00002	-0.00005
$SD_{i,t-1}$	-0.13***	0.21***	0.003***	-0.001**
$SD_{i,t-2}$	0.03*	0.16***	0.001***	-0.003***
$SD_{i,t-3}$	-0.06***	-0.04**	-0.0002	0.002***
$SD_{i,t-4}$	0.08***	0.11***	-0.00001	0.0003
$DRYZ_{i,t-1}$	6.22***	-7.15***	0.002	0.03
$DRYZ_{i,t-2}$	-6.33***	-8.52***	-0.11***	0.01
$DRYZ_{i,t-3}$	4.31***	1.84**	-0.002	-0.15***
$DRYZ_{i,t-4}$	-7.36***	-7.07***	0.05***	0.09***
$WETZ_{i,t-1}$	-0.08	-0.14	0.04***	-0.04***
$WETZ_{i,t-2}$	1.02*	1.42***	0.03***	0.09***
$WETZ_{i,t-3}$	-2.84***	-5.08***	-0.06***	-0.05***
$WETZ_{i,t-4}$	-0.11	2.72***	-0.02**	-0.07***
Fixed-Effects	Yes	Yes	Yes	Yes
R ²	0.73	0.57	0.10	0.14
N	7,259	7,259	6,636	7,259

*** $p < 0.01$, ** $p < 0.05$, * $p > 0.1$